UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

A COMPARATIVE ANALYSIS OF POPULATION DISLOCATION MODELS FOR MULTI-OBJECTIVE COMMUNITY RESILIENCE OPTIMIZATION

A THESIS

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

MASTER OF SCIENCE

By

PAUL M. CALLE CONTRERAS
Norman, Oklahoma
2019

A COMPARATIVE ANALYSIS OF POPULATION DISLOCATION MODELS FOR MULTI-OBJECTIVE COMMUNITY RESILIENCE OPTIMIZATION

A THESIS APPROVED FOR THE
GALLOGLY COLLEGE OF ENGINEERING

BY

Dr. Charles Nicholson, Chair

Dr. Shima Mohebbi

Dr. Andres Gonzalez Huertas

To my father, who encourages me to think positively

Acknowledgments

I would first like to thank my thesis advisor Dr. Nicholson for all his support for the development of this thesis. I would also like to thank my labmates at the Community Resilience Lab: Alexander Rodriguez, Yingjun Wang and Peihui Lin. Additionally, I would like to express my gratitude to my friend Dr. Hélène Peiro that helped me by reviewing part of my thesis and advising.

Finally, I must express my very profound gratitude to my father for providing me with support and continuous encouragement throughout my years of study.

Contents

List of Tables

List of Figures

Abstract

The importance of community resilience has been demonstrated by the large amount of human and economic losses from hazard events worldwide. The ability of a community to be able to recover from an event of this nature is essential for the continuity of its normal activities. Mitigation which is related with actions taking prior to a hazard event aim to decrease future consequences. Structural retrofitting is one way to diminish damage to buildings in case of an earthquake.

A Mitigation Resource Allocation (MRA) multi-objective optimization problem that decides which buildings to retrofit taking into account two objectives direct economic loss and population dislocation is studied. The case study is Shelby County, Tennessee. From literature, two population dislocation models are selected. Since it is not possible to determine that one population dislocation model is better than the other. The aim of this thesis is to explore the implications of using each population dislocation model in the MRA problem.

Chapter 1

Introduction

In 2018, the three most devastating natural disaster events were Hurricane Michael, Hurricane Florence, and the Western Wildfires-California Firestorm. Each of these three events had an estimated cost of $25 billion [2]. The amount of loss during these events demonstrates the importance of community resilience. The term resilience is defined in the Presidential Policy Directive 21 (PPD-21) [3] as "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions". PPD-21 gives directives to strengthen the security and resilience of its own critical infrastructure against both physical and cyber threats.

Natural hazards cannot be stopped; therefore, researchers and community leaders have invested in understanding and improving emergency management. Typically, the four phases of emergency preparedness are mitigation, preparedness, response, and recovery [4]. Mitigation is related with actions taken to diminish or limit the long-term damage to inhabitants and physical infrastructure. A report on the Northridge Earthquake of 1994 pointed out buildings built after 1976 were more resistant due to the upgrade in the building code [5]. This implies that it is possible to decrease hazard damages by improving structures.

Mitigation Resource Allocation (MRA) are problems where limited resources are allocated prior to a disruptive event in order to diminish the effects of the disruption. Models for different scenarios have been developed as in [6, 7, 8, 9, 10]. This work is an extension of the work performed by Zhang et al. [9] and Snelling [10]. Zhang et al. developed an earthquake MRA model for Centerville, a virtual community testbed [11], by using structural retrofitting with the objective of minimizing population dislocation and economic loss. They used a linear population dislocation function [12]. Snelling extended their work by using a nonlinear population dislocation [13, 14] for the same case study.

This thesis will develop two multi-objective MRA models for an earthquake scenario in Shelby County, Tennessee. The two objectives under consideration in both models are direct economic loss and population dislocation. Based on the existing literature, it is not possible to determine that one population dislocation model is better than the other. The first is based on an Ordinary Least Squares (OLS) regression, whereas the second is product of a logistic regression model and is thus a nonlinear function, providing probabilities that a building will dislocate. This thesis will conduct a rigorous, quantitative analysis of these two functions and in particular, the implications of the resulting Pareto fronts and solutions for the MRA decision support.

This thesis is structured as follows. Chapter 2 is the background that summarizes previous research. Chapter 3 describes the mathematical formulation and approach to solve. Chapter 4 describes the case study. Chapter 5 discusses the results obtained of applying the described methodology. Finally, Chapter 6 presents the conclusions and future work to be done.

Chapter 2

Background

2.1. Population dislocation

An important consequence of a natural hazard is population dislocation, which takes into account "the residents (that) stay away from their homes after the disaster event for at least some period of time" [14]. The first widely used population dislocation model was developed by the Federal Emergency Management Agency, inside their HAZUS system [14]. This system is able to calculate potential losses from different natural hazards such as earthquakes, floods, hurricanes, and tsunamis. This model for population dislocation assumes that it is only affected by building structural damage and housing type. However, this model lacks other important factors.

In [15], a study of migration after Hurricane Andrew provided evidence of the struggle of Black households to relocate. Lindell and Prater [16] states that the impacts of natural hazards varies according to socioeconomic characteristics, e.g. homes of lower income households are more prone to be destroyed due to lower quality construction materials and methods. In [17], for the Wilkes-Barre flood case study it was found that upper-middle class were more likely to leave their homes after the event than other classes. Models developed later took into account these characteristics. These models are include an OLS regression approach [12] and a logistic regression approach [13, 14].

The OLS regression takes into account factors at the block group level: loss due to building damage, percentage of Black population, percentage of vacant units, median household income, and percentage of housing units with 1 detached dwelling unit. Documentation is scarce about the data used and statistics of the model.

The logistic regression model uses certain factors at the individual building level: loss due to building damage and a dummy variable for the residential structure type. Additionally, the logistic regression model includes block group level factors associated with percentage of Black and Hispanic population. Data related to 1992 Hurricane Andrew was used as input for this logistic model and the logistic model has a Nagelkerke R-square of 0.205 and certain limitations. The first limitation is the source of the data, it comes a major disaster, caution should be taken when applying to events of minor to moderate severity. Second, the model was developed from socioeconomic and demographic data from Miami-Dade County. Third, there are other factors that influence population dislocation such disaster type, weather, infrastructure disruption and job loss which are not considered in their study.

The mathematical details of these population dislocation models are explained in Section 3.3.3. The linear regression and logistic regression models for population dislocation are used as one of the objectives in the MRA models developed for the case study of this thesis.

2.2. Mitigation resource allocation optimization models

Models to reduce the possible impact of natural hazards in the mitigation phase have been already developed. Shah et al. [6] developed a MRA model using Integer Programming and applied it to a small case study based on fifteen buildings taken from Standford University's database. They use 4 retrofit alternatives for each building: do nothing, retrofit to reach life safety level, retrofit to reach damage control level, and building replacement. They used a single objective that minimizes global cost, i.e. the total cost of intervention and future consequences.

Jennings et al. [7] performed a multi-objective optimization model for retrofit strategy of wood frame buildings to minimize initial cost, economic loss, number of deaths, and recovery time. The weighted sum method was used to aggregate the objectives in a single value. The retrofit policy was obtained by using a genetic algorithm and was solved for Los Angeles County California with 5000 buildings.

Dodo et al. [8] developed a linear programming model for a mitigation earthquake analysis through a period of time . They developed an application for 10 census tracts in Los Angeles County. Their objective minimized the total mitigation expenditure as well as the expected post-earthquake reconstruction cost. They analyzed the trade-off between investing in mitigation or reconstruction.

Zhang et al. [9] developed a MRA multi-objective optimization model using structural retrofit in the virtual city of Centerville. They used four code levels of retrofitting. Two objectives were minimized: direct economic loss and population dislocation. For the second objective, they used a linear function [12]. To solve this problem they used the ϵ-constraint method. This method is explained in detail in Section 3.1.2. Snelling [10] made an extension of Zhang et al. by using the nonlinear population dislocation for the same case scenario.

The present thesis will be applied to a real case scenario in Shelby county, Tennessee. The two population dislocation discussed in Section 2.1 will be used in MRA models to understand the impact in both the solution and objective space.

Chapter 3

Methodology

3.1. Multi-objective optimization algorithms

3.1.1 Multi-objective optimization

Multi-objective optimization problems deal with conflicting objectives, i.e. there is a trade-off between the objectives. Indeed, for the case of maximizing two objectives, while one objective increases the other decreases. Due to this fact, there is no unique global solution but rather a set of solutions.

In general, we are interested in the following mathematical problem:

minimize/maximize: $f_m(\mathbf{x})$, m=$1, 2, \ldots, M$;

subject to: $g_j(\mathbf{x}) \geq 0$, j=$1, 2, \ldots, J$;

$h_k(\mathbf{x}) \geq 0$, k=$1, 2, \ldots, K$;

$x_i^{(L)} \leq x_i \leq x_i^{(U)}$, i=$1, 2, \ldots, n$;

A solution $\mathbf{x}$ is a vector of n decision variables : $\mathbf{x} = (x_1, x_2, \ldots, x_n)^T$

Where there are M objective functions $f_m(\mathbf{x}) = (f_1(\mathbf{x}),\ f_2(\mathbf{x}),\ \ldots\ ,\ f_M(\mathbf{x}))$ to be minimized/maximized. Furthermore, the problem is subject to J inequality constraints and K equality constraints. Additionally, each variable x_i has a lower bound $x_i^{(L)}$ and upper bound $x_i^{(U)}$.

A solution that satisfies all constraints and variable bounds is called a feasible solution. The set of all feasible solutions S is called the feasible region (also named search space). The objective space is constituted by the possible values of the M objective functions for all solutions in S.

Domination

According to [1], a solution $\mathbf{x}^{(1)}$ is said to dominate another solution $\mathbf{x}^{(2)}$ if both condition 1 and 2 below are true:

Condition 1: $\mathbf{x}^{(1)}$ is no worse than $\mathbf{x}^{(2)}$ for all objectives.

Condition 2: $\mathbf{x}^{(1)}$ is strictly better than $\mathbf{x}^{(2)}$ in at least one objective.

The mathematical notation for $\mathbf{x}^{(1)}$ dominates $\mathbf{x}^{(2)}$ is: $\mathbf{x}^{(1)} \preceq \mathbf{x}^{(2)}$.

Non-dominated set:

According to [1], among a set of solutions P, the non-dominated set of solutions P' are those that are not dominated by any member of the set P.

Globally Pareto-optimal set:

According to [1], the globally Pareto-optimal set is the non-dominated set of the entire feasible search space S. It is often referred as Pareto-optimal set.

Pareto-optimal front:

According to [1], the curve formed by joining the globally Pareto-optimal solutions is known as a Pareto-optimal front. It is often referred as Pareto front.

Pareto set approximation:

Due to the stochastic nature of evolutionary algorithms, the solutions will be near or around the Pareto-optimal set. Therefore, the obtained solutions are referred to as the Pareto set approximation.

3.1.2 Solution methods

Deb [1] called the non-evolutionary algorithms for multi-objective optimization problems classical methods. The classical methods use a single solution update in every iteration and primarily use a deterministic transition rule. The classification of these methods according to [18] is as follows:

- No-preference methods: the opinion of the decision maker is not taken into consideration.
- Posteriori methods: use preference information of each objective and iteratively generate a set of Pareto-optimal solutions.
- A priori methods: Preference information of each objective is used and usually one preferred Pareto-optimal solution is found.
- Interactive methods: use preference information progressively.

In [1], the author stated the difficulties with classical methods: dependence on the initial iteration for the optimal solution which results sometimes in local optimum, inefficiency with discrete search space, and the fact that parallel machine cannot be effectively used.

ϵ-constraint Method

The ϵ-constraint is a posteriori method which optimizes one of the objectives and keeps the remaining M-1 objectives within user-specified values.

The ϵ-constraint method has the advantage of being able to deal with problems of convex and nonconvex objective spaces alike.

A description of a minimization problem using ϵ-constraint method is as follows:

Minimize: $f_\mu(\mathbf{x})$

subject to: $f_m(\mathbf{x}) \leq \epsilon_m$, m=$1, 2, \ldots$,M and $m \neq \mu$

$g_j(\mathbf{x}) \geq 0$, j=$1, 2, \ldots, J$;

$h_k(\mathbf{x}) = 0$, k=$1, 2, \ldots, K$;

$x_i^{(L)} \leq x_i \leq x_i^{(U)}$, i=$1, 2, \ldots, n$;

The function to be minimized is f_μ. The parameter ϵ_m represents an upper bound for the rest of the functions f_m. Appropriate values for ϵ_m should be used. Similar to the general formulation, the problem is subject to J inequality constraints and K equality constraints. Similarly, the variables have upper and lower bounds.

NSGA-II

Multi-objective evolutionary algorithms (MOEA) can be subdivided in non-elitist and elitist algorithms. Eliticism consists in promoting the best individual of a population to the next generation. According to [1], "elitist multi-objective evolutionary algorithms are supposedly faster and better (than non-elitist MOEA)".

There are a large variety of elitist MOEA. There is no one MOEA algorithm that outperforms the others in all problems. However, I will use an elitist non-dominated sorting GA (called NSGA-II) [19] because of its widespread implementation [20, 21] and its focus in finding diverse solutions. NSGA-II is an MOEA that has the following three features:

1. It uses an elitist principle, i.e. the elites of a population are given the opportunity to be carried to the next generation.
2. It uses an explicit diversity preserving mechanism (Crowding distance). This supports a wide range of solutions.
3. It emphasizes the non-dominated solutions.

A brief summary of the procedure for NSGA-II taken from [1] is as follows:

1. Perform a non-dominated sorting in the combination (R_t) of parent and offspring populations, P_t and Q_t, respectively. Classify them by fronts, i.e. they are sorted according to an ascending level of non-domination (F_1, F_2, F_3 ...).
2. Fill the new population P_{t+1} with fronts according to the front raking in which solutions belonging to the least dominated fronts are selected first. If there are more solutions in a front that can fit in the new population, then sort the solution in the front with respect to the "crowding distance" (a distance related to the density of solutions around each solution). The greater crowding distances are preferred.

3. Create an offspring population Q_{t+1} from P_{t+1} using crowded tournament selection (comparing by front ranking, if equal then by crowding distance), crossover, and mutation operators.

A schema of the procedure can be seen in Fig. 3.1.

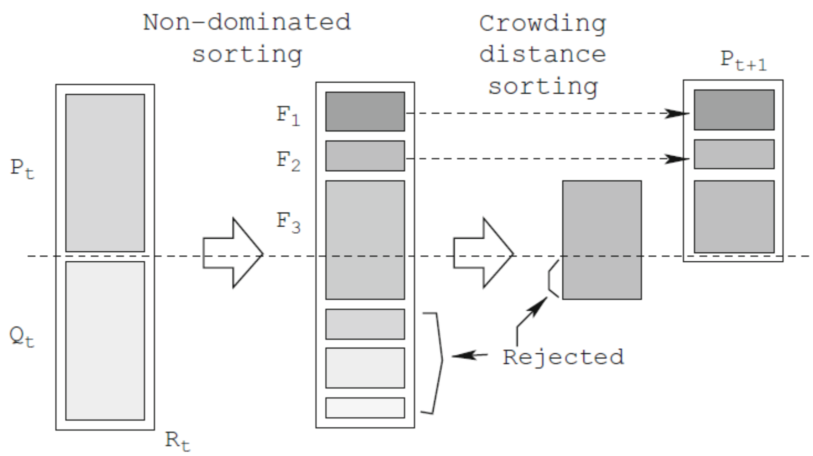

Figure 3.1: Schematic of the NSGA-II procedure [1].

3.2. Methods of comparison

In order to compare different solutions of multi-objective optimization problems, [22] states that there are three approaches that allow to assess the performance of stochastic multi-objective optimizers: dominance ranking, quality indicators, and attainment functions. The first approach collects all the Pareto set approximations obtained by the different algorithms, conducts pairwise comparisons and ranks them according to the number of sets that each set dominates. For the second approach, the quality indicator compress the information of the Pareto set approximation into a real value. This property allows the comparison of approximation sets through the obtained values. The third approach employs the empirical attainment function which condenses the results of multiple runs of one algorithm through the use of a probability density function.

In this work, the second approach (quality indicators) will be used. This is motivated by its wide used, e.g. [23, 24, 25]. The hypervolume indicator I_h proposed by [26] will be used. This indicator measures the hypervolume enclosed by an approximation set and a reference point that is (at least weakly) dominated by all points. In Figure 3.2, the approximation set A contains the points (3,10), (5,4) and (8,2). The area surrounded is the hypervolume with respect to reference point (15,15).

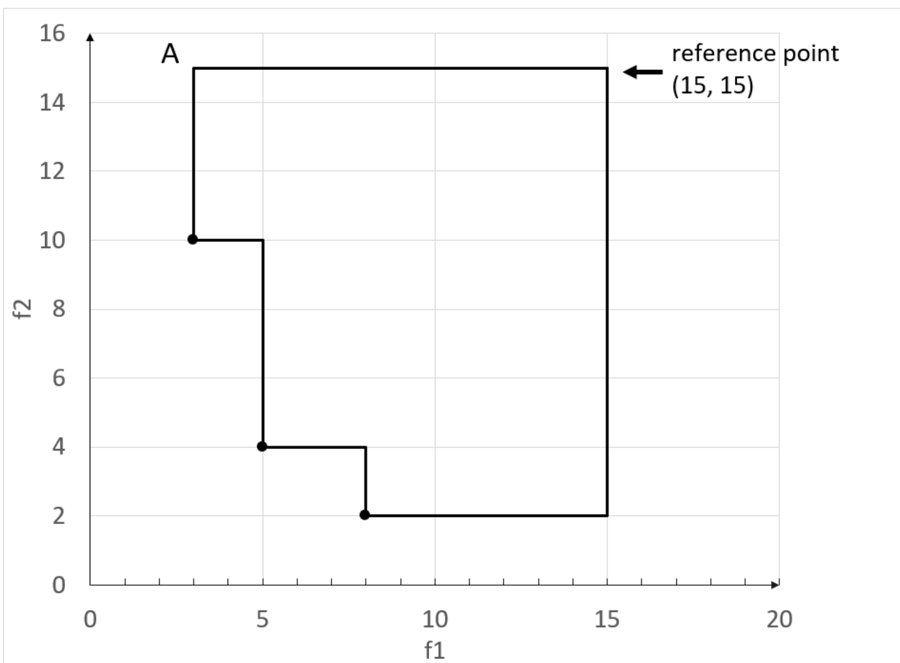

Figure 3.2: Example of the hypervolume indicator. For this set A the indicator value $I_H(A) = 134$; the point (15,15) is taken as the reference point.

3.3. Optimization model

3.3.1 Important terms

According to U.S. Census Bureau, Public Use Microdata Areas (PUMAs) are statistical geographic areas defined for the dissemination of the characteristic of each housing unit and person in it. Each PUMA contains at least 100,000 people. The county of study, Shelby is divide in 8 PUMAs. The effect of the solution in each PUMA will be evaluated.

According to U.S. Census Bureau, block groups are statistical divisions that are generally defined to contain among 600 and 3000 people [27]. Statistics provided by the Census Bureau are at block group level.

3.3.2 Scope

The mitigation is performed through structural retrofitting i.e. perform modifications to the structures in order to diminish risk of future damage and protect the life of inhabitants. The structural retrofitting decisions are not at the building level. Buildings are grouped into categories based on block groups, PUMA, occupation type (single family, multi family dwelling, etc.), structure type (wood light frame, steel moment frame mid-rise, etc.) and code level (related with seismic design level: Pre-code, Low-Code, Moderate-Code and High-Code).

Due to data limitations, a small percentage of buildings are associated with 2 PUMAs. Therefore, I decided to make the decision variable that indicates the number of buildings in a specific configuration a real value. When the linear population dislocation is used as one of the objectives, it results in a linear programming problem. The ϵ-constraint method is used to solve it. Whereas, when the non-linear population dislocation is utilized the NSGA-II method is used. Both methods are explained in Section 3.1.2.

3.3.3 Model formulation

Objectives

For this thesis, the following nomenclature is used, let $\mathcal{B}$ denote the set of block groups, $\mathcal{P}$ denotes the set of PUMAs, $\mathcal{C}$ denote the set of occupation types, $\mathcal{S}$ denote the set of structure types, and $\mathcal{K}$ denote the set of ordered code levels.

Let the decision variable x_{ijklm} denote the total number of buildings in block group $i \in \mathcal{B}$, in PUMA $j \in \mathcal{P}$, of occupation type $k \in \mathcal{C}$, of structure type $l \in \mathcal{S}$, at code level $m \in \mathcal{K}$ after retrofitting. The parameter b_{ijklm} reflects the corresponding quantity of buildings prior to any mitigation effort. The difference between x_{ijklm} and b_{ijklm} indicates the retrofit policy.

Direct economic loss is calculated as shown in Equation 3.1, where l_{ijklm} denotes the expected direct economic loss of a structure due to the scenario of an earthquake.

$$\min \sum_{i \in \mathcal{B}} \sum_{j \in \mathcal{P}} \sum_{k \in \mathcal{C}} \sum_{l \in \mathcal{S}} \sum_{m \in \mathcal{K}} l_{ijklm} \times x_{ijklm} \tag{3.1}$$

The second objective is population dislocation. For this objective two models will be used. The first model is product of an Ordinary Least Squares regression [12]. The population dislocation d_i for a block group i is:

$$d_i = t_i \times \%vloss_i \times (\beta_1 + \beta_2 \times \%b_i + \beta_3 \times \%v_i + \beta_4 \times m_i + \beta_5 \times \%s_i) \quad , \forall i \in \mathcal{B} \tag{3.2}$$

In Equation 3.2, t_i denotes the number of households in block group i. The regression coefficients, $\beta_1, \ldots, \beta_5$ are .995, -0.003, -0.14, 0.11 ,and -0.03 respectively. The variables $\%b_i$, $\%v_i$, m_i, and $\%s_i$ denotes the zone characteristics: percentage of black population, percentage of vacant housing units, median household income in thousand dollars, and single-family detached housing percentage respectively.

The average percent building value loss in block group i $\%vloss_i$ is calculated as:

$$\%vloss_i = \frac{\sum_{j\in\mathcal{P}}\sum_{k\in\mathcal{C}}\sum_{l\in\mathcal{S}}\sum_{m\in\mathcal{K}} l^{-c}_{ijklm} \times x_{ijklm}}{\sum_{j\in\mathcal{P}}\sum_{k\in\mathcal{C}}\sum_{l\in\mathcal{S}}\sum_{m\in\mathcal{K}} \bar{M}_{ijkl} \times b_{ijklm}} \times 100 \quad \forall i \in \mathcal{B} \tag{3.3}$$

In Equation 3.3, l^{-c}_{ijklm} denotes the direct economic loss of a building excluding content loss. M_{ijkl} indicates the average appraised value per building for buildings grouped in block group $i \in \mathcal{B}$, in PUMA $j \in \mathcal{P}$, of occupation type $k \in \mathcal{C}$, of structure type $l \in \mathcal{S}$.

The second model for population dislocation is nonlinear product of a logistic regression [13, 14]. The probability of dislocation $probDisl_{ijklm}$ for a given $i \in \mathcal{B}$, $j \in \mathcal{P}$, $k \in \mathcal{C}$, $l \in \mathcal{S}$, and $m \in \mathcal{K}$:

$$probDisl_{ijklm} = \frac{1}{1 + e^{-[\beta_0 + \beta_1 \times \%vloss_{ijklm} + \beta_2 \times DS_l + \beta_3 \times \%B_i + \beta_4 \times \%H_i]}} \tag{3.4}$$

In Equation 3.4, the regression coefficients $\beta_0, \ldots, \beta_4$ are -.42523, 0.02480, -0.50166, -0.01826, and -0.01198 respectively. $\%vloss_{ijklm}$ represents percentage value loss of a building. The terms DS_l, $\%B_i$, and $\%H_i$ are respectively the dummy variable for residential structure, percentage of Black population, and percentage of Hispanic population.

$$\%vloss_{ijklm} = \frac{l^{-c}_{ijklm}}{\bar{M}_{ijkl}} \times 100 \tag{3.5}$$

The term $\%vloss_{ijklm}$ can be calculating using Equation 3.5. The terms l^{-c}_{ijklm} and M_{ijkl} have the same meaning as in Equation 3.3.

With respect to the dummy variable DS_l, it takes the following values:

- $DS_l = 1$, if occupation type is RES1 (Single Family Dwelling)
- $DS_l = 0$, if occupation type is RES3 (Multi Family Dwelling)

With this probability, the term DF_{ijklm} (dislocation factor) for a given $i \in \mathcal{B}$, $j \in \mathcal{P}$, $k \in \mathcal{C}$, $l \in \mathcal{S}$, and $m \in \mathcal{K}$ is computed.

- $DF_{ijklm} = 1$ if $probDisl_{ijklm} \geq threshold$
- $DF_{ijklm} = 0$ if $probDisl_{ijklm} < threshold$

Where the default value of *threshold* is 0.5. However, this value can be adjusted according to different characteristics of the natural hazard, weather conditions, and infrastructure disruptions [14].

The term DF_{ijklm} is then used to calculate the dislocation per block group d_i:

$$d_i = \sum_{j \in \mathcal{P}} \sum_{k \in \mathcal{C}} \sum_{l \in \mathcal{S}} \sum_{m \in \mathcal{K}} x_{ijklm} \times DF_{ijklm} \times nDU_{ijkl} \times aveHhDU_i \tag{3.6}$$

Where nDU_{ijkl} is average number of dwelling units. The term $aveHhDU_i$ is the average number of households per dwelling units for block group i.

The objective is to minimize the total population dislocation, that is calculated as follows:

$$\min \sum_{i \in \mathcal{B}} d_i \tag{3.7}$$

Constraints

Population dislocation does not have the same impact in all socioeconomic levels. In order to restrict the disparity of population dislocation among different income levels a constraint is required. First the initial disparity $\bar{D}$ is calculated as follows:

$$\bar{D} = \sum_{i \in R_h} \bar{d}_i - \sum_{i \in R_m} \bar{d}_i + \sum_{i \in R_h} \bar{d}_i - \sum_{i \in R_l} \bar{d}_i + \sum_{i \in R_m} \bar{d}_i - \sum_{i \in R_l} \bar{d}_i \tag{3.8}$$

In Equation 3.8, $\bar{D}$ is calculated as the difference of dislocation among different income categories. Where $\bar{d}_i$ is the population dislocation for a specific block group i under the assumption that no residential building retrofits are implemented. Each block group i belongs to any of the following income categories: high-income $\mathcal{R}_h$, medium-income $\mathcal{R}_m$, and low-income $\mathcal{R}_l$ respectively.

$$\sum_{i \in R_h} d_i - \sum_{i \in R_m} d_i + \sum_{i \in R_h} d_i - \sum_{i \in R_l} d_i + \sum_{i \in R_m} d_i - \sum_{i \in R_l} d_i \leq \bar{D} \tag{3.9}$$

The constraint that the disparity of any solution should be less than the initial disparity is taken into account in Equation 3.9.

Another constraint is the budget B. An important assumption is made, the cost of the retrofit is included in the assessed value of the building, that is, if a given structure in block group i in PUMA j with occupation type k, structure type l and code level m has an assessed value of M_{ijklm}. If it is retrofit to a higher level, $m^* > m$, then the cost of the corresponding retrofit is assumed to be the difference in the values, $M_{ijklm^*} - M_{ijklm}$. The budget constraint is taken into account in Equation 3.10.

$$\sum_{i\in\mathcal{B}}\sum_{j\in\mathcal{P}}\sum_{k\in\mathcal{C}}\sum_{l\in\mathcal{S}}\sum_{m\in\mathcal{K}} M_{ijklm}\times(x_{ijklm}-b_{ijklm})\leq B \tag{3.10}$$

Another constraint is related with the improvement of code level. The sum of m from 0 up to m^* for b_{ijklm} serves us an upper bound for the sum of m from 0 up to m^* of x_{ijklm}. This makes sure the buildings are only allowed to improve in code level.

$$\sum_{m=0}^{m^*} x_{ijklm}\leq\sum_{m=0}^{m^*} b_{ijklm},\ \forall i\in\mathcal{B},\ j\in\mathcal{P},\ k\in\mathcal{C},\ l\in\mathcal{S},\ m^*\in\mathcal{K} \tag{3.11}$$

Finally, the total number of buildings for a given $i\in\mathcal{B}$, $j\in\mathcal{P}$, $k\in\mathcal{C}$, and $l\in\mathcal{S}$ across code levels should be the same for the decision variable and base case:

$$\sum_{m\in\mathcal{K}} x_{ijklm}=\sum_{m\in\mathcal{K}} b_{ijklm} \tag{3.12}$$

The final summary of the model is as follows:

$$\min\sum_{i\in\mathcal{B}}\sum_{j\in\mathcal{P}}\sum_{k\in\mathcal{C}}\sum_{l\in\mathcal{S}}\sum_{m\in\mathcal{K}} l_{ijklm}\times x_{ijklm}$$

$$\min\sum_{i\in\mathcal{B}} d_i$$

Linear population dislocation:

$$d_i=t_i\times\%vloss_i\times(\beta_1+\beta_2\times\%b_i+\beta_3\times\%v_i+\beta_4\times m_i+\beta_5\times\%s_i)\quad,\forall i\in\mathcal{B}$$

$$\%vloss_i=\frac{\sum_{j\in\mathcal{P}}\sum_{k\in\mathcal{C}}\sum_{l\in\mathcal{S}}\sum_{m\in\mathcal{K}} l_{ijklm}^{-c}\times x_{ijklm}}{\sum_{j\in\mathcal{P}}\sum_{k\in\mathcal{C}}\sum_{l\in\mathcal{S}}\sum_{m\in\mathcal{K}} \bar{M}_{ijkl}\times b_{ijklm}}\times 100\quad\forall i\in\mathcal{B}$$

Nonlinear population dislocation:

$$probDisl_{ijklm} = \frac{1}{1 + e^{-[\beta_0 + \beta_1 \times \%vloss_{ijklm} + \beta_2 \times DS_l + \beta_3 \times \%B_i + \beta_4 \times \%H_i]}}$$

$$\%vloss_{ijklm} = \frac{l_{ijklm}^{-c}}{\bar{M}_{ijkl}} \times 100$$

- $DF_{ijklm} = 1$ if $probDisl_{ijklm} \geq threshold$
- $DF_{ijklm} = 0$ if $probDisl_{ijklm} < threshold$

$$\%vloss_{ijklm} = \frac{l_{ijklm}^{-c}}{\bar{M}_{ijkl}} \times 100$$

$$d_i = \sum_{j \in \mathcal{P}} \sum_{k \in \mathcal{C}} \sum_{l \in \mathcal{S}} \sum_{m \in \mathcal{K}} x_{ijklm} \times DF_{ijklm} \times nDU_{ijkl} \times aveHhDU_i$$

Constraints:

$$\bar{D} = \sum_{i \in R_h} \bar{d}_i - \sum_{i \in R_m} \bar{d}_i + \sum_{i \in R_h} \bar{d}_i - \sum_{i \in R_l} \bar{d}_i + \sum_{i \in R_m} \bar{d}_i - \sum_{i \in R_l} \bar{d}_i$$

$$\sum_{i \in R_h} d_i - \sum_{i \in R_m} d_i + \sum_{i \in R_h} d_i - \sum_{i \in R_l} d_i + \sum_{i \in R_m} d_i - \sum_{i \in R_l} d_i \leq \bar{D}$$

$$\sum_{i \in \mathcal{B}} \sum_{j \in \mathcal{P}} \sum_{k \in \mathcal{C}} \sum_{l \in \mathcal{S}} \sum_{m \in \mathcal{K}} M_{ijklm} \times (x_{ijklm} - b_{ijklm}) \leq B$$

$$\sum_{m=0}^{m^*} x_{ijklm} \leq \sum_{m=0}^{m^*} b_{ijklm}, \forall i \in \mathcal{B},\ j \in \mathcal{P},\ k \in \mathcal{C},\ l \in \mathcal{S},\ m^* \in \mathcal{K}$$

$$\sum_{m \in \mathcal{K}} x_{ijklm} = \sum_{m \in \mathcal{K}} b_{ijklm}$$

Chapter 4

Case study

4.1. Shelby county

The application of these models takes place in Shelby County, a county in the US state of Tennessee. The location of Shelby County in the state of Tennessee is shown in Figure 4.1. This is due to the fact of the availability of data. The county has about 300,000 households. The county is divided into 625 block groups, 8 PUMAs (3201, 3202, ..., 3208), 19 occupation types subdivided into 3 categories residential, commercial and industrial. The distribution of PUMAs in Shelby county is displayed in Figure 4.2. Additionally, 11 structure types and 4 code levels. Finally, each block group belongs to an income level (low, medium, and high) according to its median household income. The descriptions for occupation type is found in Table 4.1, for structure types in Table 4.2, for code level in Table 4.3, and for income levels in Table 4.8. The descriptions were taken from [28].

The distribution of buildings and percentages by PUMA, occupation type, structure type, and code level can be found in Table 4.4, 4.5, 4.6, and 4.7, respectively.

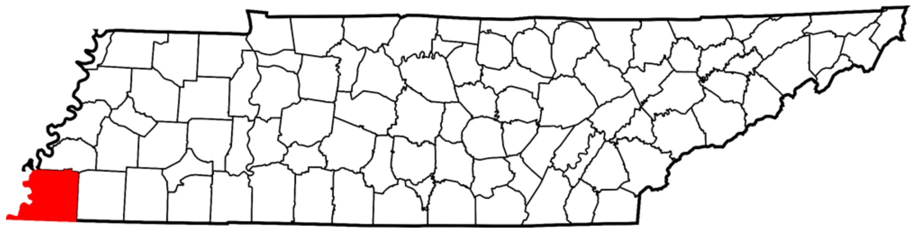

Figure 4.1: Location in Shelby County in the state of Tennessee.

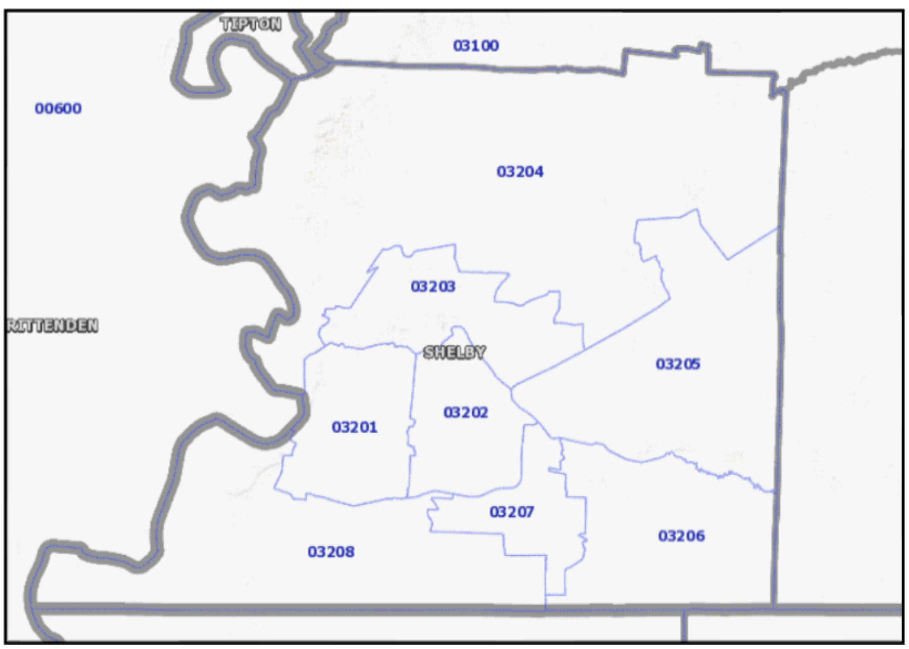

Figure 4.2: PUMAs in Shelby County

From Table 4.5, it can be observed that around 89% of total buildings belong to Single Family Dwelling (RES1). Table 4.6 shows that structure type Wood, Light Frame ($\leq$ 5,000 sq. ft.) is present in 89% of the buildings. From Table 4.7, 93% of the buildings initially are at Low-Code Level(2). Additionally, from Table 4.8 it can be observed that 55% belong to medium income level.

Furthermore, in Tables 4.9 and 4.10 shows the distribution of appraised value and number of households according to PUMA and income level, respectively.

Occupation type	Occupation Class	Description
COM1	Retail Trade	Store
COM2	Wholesale Trade	Warehouse
COM3	Personal and Repair Services	Service Station/Shop
COM4	Professional/Technical Services	Offices
COM5	Banks/Financial Institutions	
COM6	Hospital	
COM7	Medical Office/Clinic	Offices
COM8	Entertainment and Recreation	
COM9	Theaters	
COM10	Parking	Garages
IND1	Heavy	Factory
IND2	Light	Factory
IND4	Metals/Minerals Processing	Factory
IND5	High Technology	Office
RES1	Single Family Dwelling	Detached House
RES2	Mobile Home	Mobile Home
RES3	Multi Family Dwelling	Apartment/Condominium
RES4	Temporary Lodging	Hotel/Motel
RES5	Institutional Dormitory	Groups Housing (military, college), Jails
RES6	Nursing Home	

Table 4.1: Occupation types

Label	Description
C1	Concrete Moment Frame
C2	Concrete Shear Walls
MH	Mobile Homes
PC1	Precast Concrete Tilt-Up Walls
PC2	Precast Concrete Frames with Concrete Shear Walls
RM	Reinforced Masonry Bearing Walls
S1	Steel Moment Frame
S3	Steel Light Frame
URM	Unreinforced Masonry Bearing Walls
W1	Wood, Light Frame ($\leq$ 5,000 sq. ft.)
W2	Wood, Commercial and Industrial ($\geq$ 5,000 sq. ft.)

Table 4.2: Structure types

Seismic Design Level	Assign number
Pre-Code	1
Low-Code	2
Moderate-Code	3
High-Code	4

Table 4.3: Seismic design level

PUMA	Buildings	Percentage
3201	51,780	17.0%
3202	49,589	16.3%
3203	36,089	11.9%
3204	32,995	10.9%
3205	32,196	10.6%
3206	38,410	12.6%
3207	28,056	9.2%
3208	34,720	11.4%

Table 4.4: Distribution by PUMAs

Occupation type	Buildings	Percentage
COM1	3,989	1.31%
COM2	4,623	1.52%
COM3	1,540	0.51%
COM4	2,860	0.94%
COM5	219	0.07%
COM6	22	0.01%
COM7	407	0.13%
COM8	1,302	0.43%
COM9	27	0.01%
COM10	49	0.02%
IND1	638	0.21%
IND2	313	0.10%
IND4	27	0.01%
IND5	13	0.00%
RES1	269,313	88.64%
RES2	43	0.01%
RES3	18,016	5.93%
RES4	298	0.10%
RES5	54	0.02%
RES6	85	0.03%

Table 4.5: Distribution by Occupation type

Structure type	Buildings	Percentage
C1	593	0.20%
C2	80	0.03%
MH	43	0.01%
PC1	1,045	0.34%
PC2	34	0.01%
RM	1,564	0.51%
S1	3,428	1.13%
S3	3,249	1.07%
URM	11,028	3.63%
W1	271,590	89.39%
W2	11,182	3.68%

Table 4.6: Distribution by Structure types

Code Level	Buildings	Percentage
1	5,848	1.9%
2	283,589	93.3%
3	1,244	4.1%
4	1,956	0.6%

Table 4.7: Initial distribution by code level

Income Level	Buildings	Percentage
Low	105,039	34.6%
Medium	168,848	55.6%
High	29,948	9.9%

Table 4.8: Initial distribution by income level

PUMA	Appraised value ($ millions)	Households
3201	4,957	60,265
3202	6,725	51,328
3203	3,744	41,307
3204	5,416	35,610
3205	6,245	40,619
3206	9,256	44,698
3207	4,795	40,207
3208	4,488	36,650
Total	45,625	350,685

Table 4.9: Appraised value ($ millions) and households by PUMAs

4.2. Input Data

The data for Shelby County was obtained from different sources. Information about appraised value, buildings, PUMA, sector, structure type, and occupation type was obtained by the Center for Risk-Based Community Resilience Planning.

Income Level	Appraised value ($ millions)	Households
Low	9,301	124,996
Medium	26,920	194,885
High	9,404	30,804

Table 4.10: Appraised value ($ millions) and households by income level

Census data like ethnicity, housing units, households, different income levels, occupancy status of housing units and median household income per block group was obtained from the data retrieval product American FactFinder from the United States Census Bureau [29]. This system is publicly available.

4.2.1 Hazard simulation

The estimation of economic loss values for Shelby County was obtained from simulations run by Peihui Lin at the University of Oklahoma. The scenario was an earthquake of magnitude 7.7 and an epicenter located at 35.3 N; 90.3 W (on the New Madrid Fault Line). More details about economic loss can be found in [30].

4.2.2 Retrofit cost

Similar to [9], I consider the cost of the retrofit implementation to be part of the appraised value as it gives a reasonable approximation. A percentage relation is used to indicated the difference among code levels. An enhancement from code level 1 (Pre-Code) to 2 (Low-Code) implies a cost of 1% of the appraised value, to 3 (Moderate-Code) implies 5%, and to 4 (High-Code) a 8%.

4.3. Solution approach

When solving the multi-objective optimization problem and using the linear population dislocation objective, the ϵ-constraint method will be used. Additionally, when the non-linear population dislocation is used, NSGA-II will be utilized to solve the problem.

A third model that uses the results of the ϵ-constraint method solution as a initial population for NSGA-II will be implemented.

Chapter 5

Results and analysis

This chapter is organized as follows. In the first section, the baseline scenario for economic loss is shown before performing structural retrofitting; the second section considers the initial linear population dislocation and the results of the MRA using the linear population dislocation as an objective. The solutions for three budgets are presented. In the third section, the initial population dislocation for different thresholds is shown. Additionally, for the MRA model with nonlinear population dislocation as one objective explore the effect of different thresholds for a specific budget. Finally, the fourth section compares and contrast the results of both models.

5.1. Baseline scenario economic loss

The total baseline direct economic loss (without retrofit intervention) is $11.5B. Figure 5.1 shows the direct economic loss in millions of $. Similarly, Figure 5.2 displays the same characteristic by income level. The values of percentage loss respect to appraised value by PUMA and income level is shown in Table 5.1 and 5.2. It can be observed that PUMA 3201 has the largest economic loss with respect to its appraised value 43.8% and PUMA 3206 has the lowest. For the case of income, even though medium income level has the largest absolute value of direct economic loss, the percentage of loss respect to appraised is the largest for the low income group.

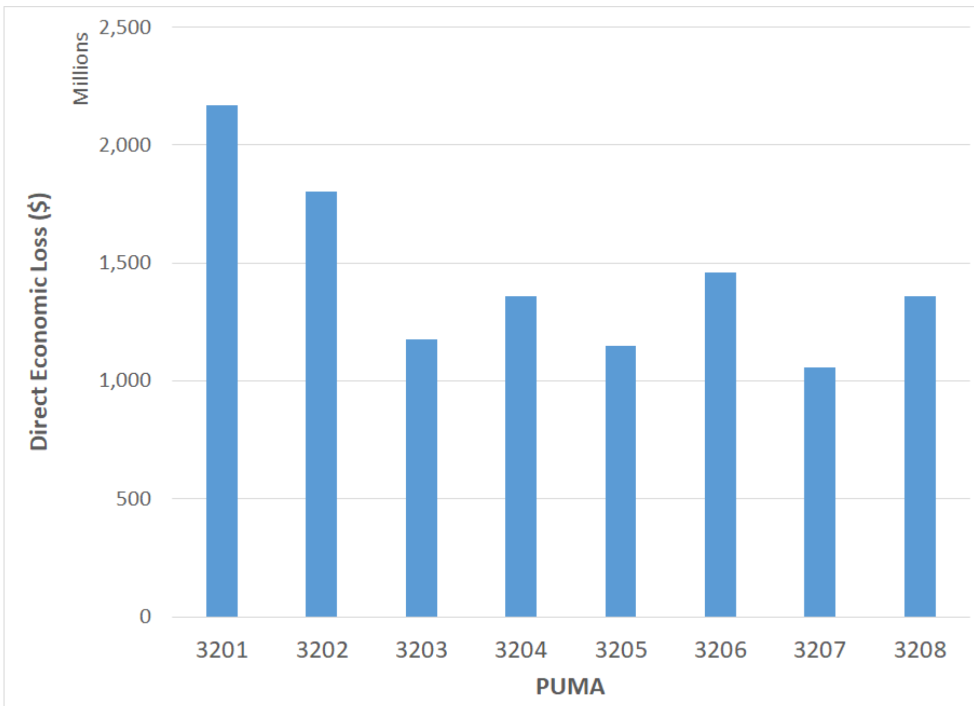

Figure 5.1: Direct economic loss by PUMA

5.2. Using linear population dislocation

The total baseline number of dislocated household by using the linear population dislocation model is 86,907 which account for the 24.8% of total households. The manner in which is split according to PUMA and income level can be found in

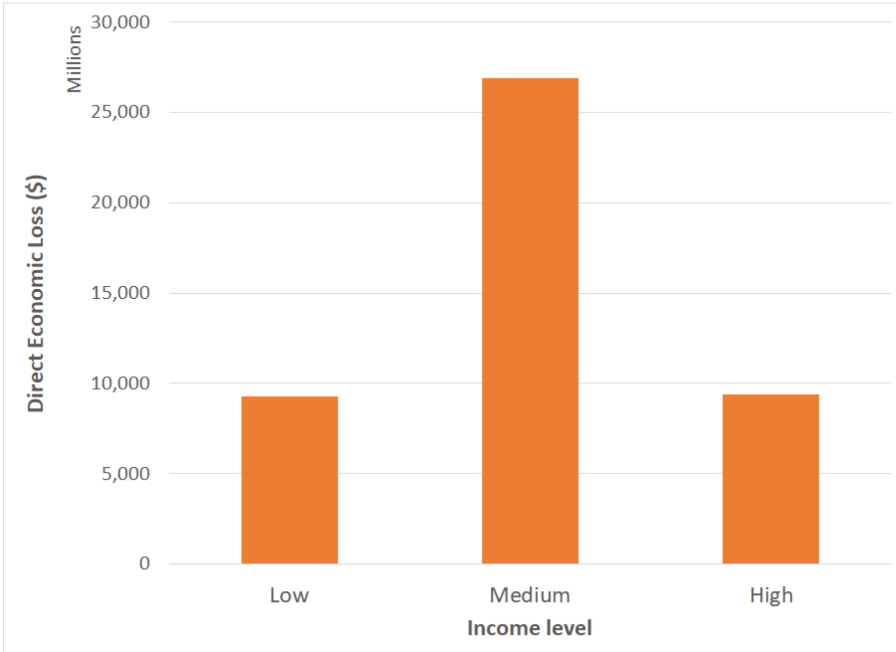

Figure 5.2: Initial direct economic loss and percentage respect to appraised value by PUMA

PUMA	%Loss
3201	43.8%
3202	26.8%
3203	31.4%
3204	25.1%
3205	18.4%
3206	15.8%
3207	22.0%
3208	30.3%

Table 5.1: % Percentage of initial percentage of economic loss with respect to appraised value by PUMA

Table 5.3 and 5.4, respectively. It can be noted that the percentage of households dislocated per PUMA is within the range of 16.8% to 31.5%.

The ideal budget can be calculated by retrofitting the buildings to their maximum code level possible. With the exception of Unreinforced Masonry Bearing Walls

Income Level	%Loss
Low	34.4%
Medium	24.8%
High	17.6%

Table 5.2: % Percentage of initial percentage of economic loss with respect to appraised value by income level

PUMA	% Household dislocated
3201	24.4%
3202	29.8%
3203	26.0%
3204	31.5%
3205	24.5%
3206	24.3%
3207	16.8%
3208	20.1%

Table 5.3: % Percentage of initial dislocated households by PUMA for linear population dislocation

Income level	% Household dislocated
Low	17.3%
Medium	27.8%
High	36.0%

Table 5.4: % Percentage of initial dislocated households by income level

(URM), each of the structure types can be improved to the High-code level . For URM, due to current standards such structures can be retrofit only up to the Low-code level. The cost to upgrade every building from its current status to the highest possible level is computed to be $2.6B. The solutions for specific budgets constraints will be analyzed. These budgets are 15%, 30%, and 60% respect to the ideal budget ($392M, $784M, and $1.6B, respectively).

To solve this MRA problem, the ϵ-constraint method is used.Population dislocation is minimized whereas direct economic loss is used as a constraint through the used of ϵ. Since it is possible to pre-calculate the minimum and maximum for direct economic loss, we can allows set an appropriate range for ϵ. For each percentage it took around 50 minutes on a computer with an Intel Xeon E5-2670 processor running at 2.60Ghz.

In Figure 5.3, the solution for each budget constraint is shown. From it, it can be said that a larger value of budget allows to reduce more the population dislocation as well as the economic loss. A middle point for each curve is highlighted for comparison. The percentage reduction from baseline scenario for the mentioned points can be observed in Table 5.5.

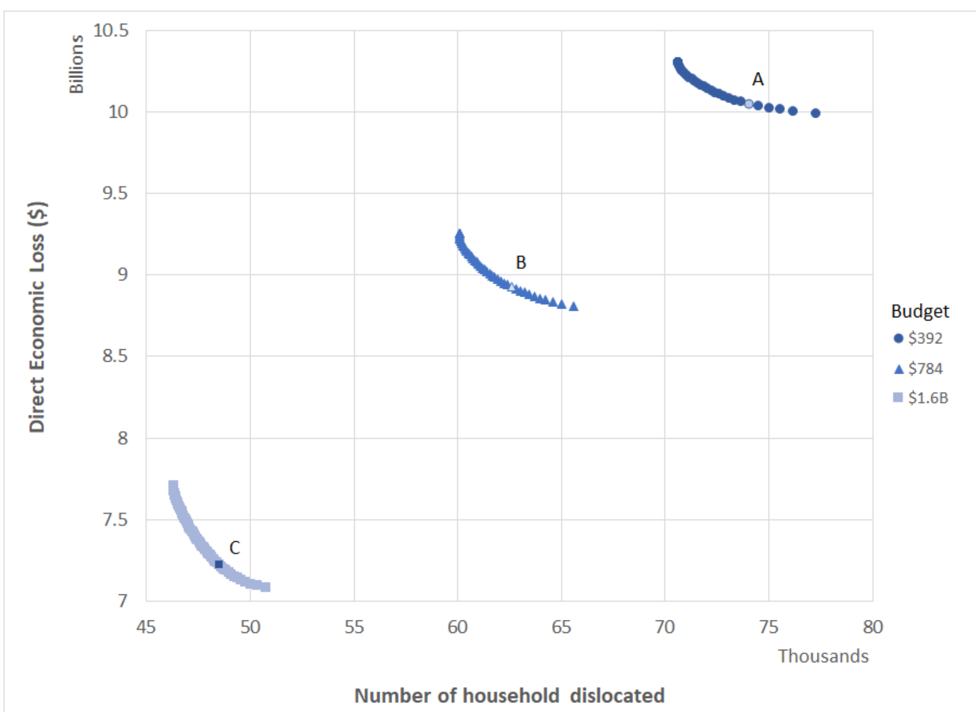

Figure 5.3: Results of Pareto optimal set for budgets $329M, $784M, and $1.6B for linear regression population dislocation.

Table 5.6 reports the minimum, maximum, and range for each objective with respect to each budget constraint. At \$392M budget constraint, by comparing the extreme points the decision maker faces a choice between 6,641 dislocated households or a loss of \$313M . Similarly, for the highest budget \$1.6B the choice is between 4,469 dislocated households or \$629M.

5.3. Using nonlinear population dislocation

The parameter used to solve the NSGA-II problem are displayed in Table 5.10. For population size and number of generations I chose values that I considered suitable. While for crossover and mutation rate, I arrived to those values after trying different options .The initial percentage of dislocated household per threshold is shown in Table 5.7. The distribution of percentage of dislocated household by PUMA and income level are displayed in Table 5.8 and 5.9. From Table 5.7, it can be observed that the higher the threshold, the smaller population dislocation. It can be inferred from Table 5.8 that PUMA 3208 has the least percentage of dislocated households through thresholds. An important observation is that for threshold 0.30 the largest percentage of dislocated household for a specific PUMA is for PUMA 3202 whereas for threshold 0.5 the largest corresponds to 3201.

The initial values of percentage for each threshold is shown in Table 5.7. Additionally, Table 5.8 and 5.9 show the percentage of dislocated housed by PUMA and income level, respectively. Higher values of number of dislocated households is obtained from smaller values of thresholds.

To solve the nonlinear optimization problem, NSGA-II is used. At first, random solution values in the NSGA-II algorithm were used as the initial populations.

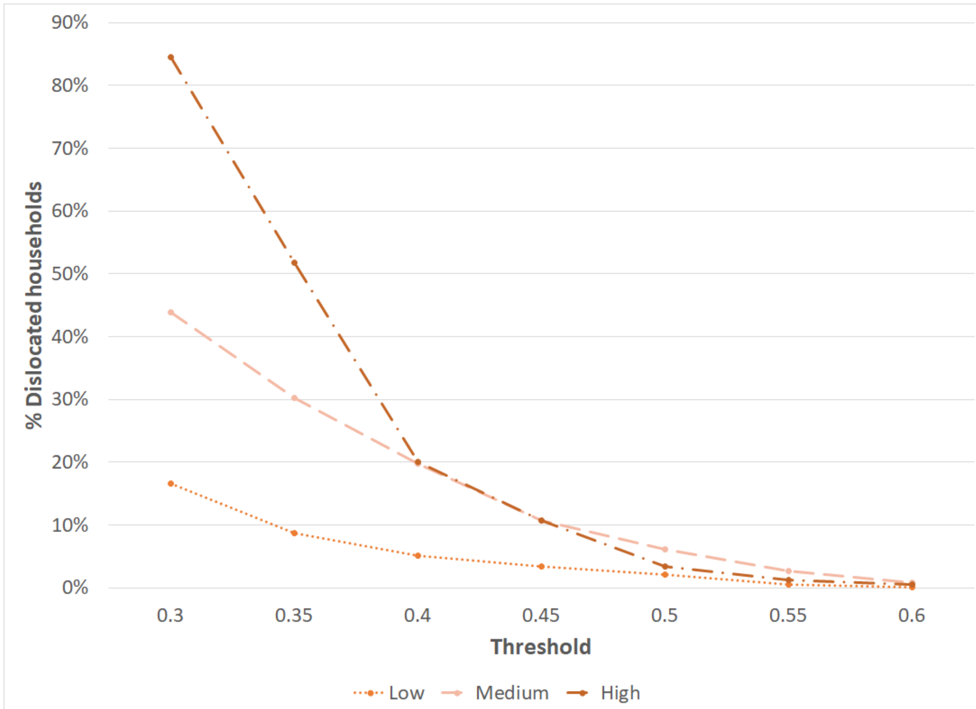

Figure 5.4: Change in percentage by threshold and income level for initial non-linear population dislocation

However, this leads to a slow convergence. Taking this into account, the solutions obtained from the OLS ϵ-constraint method (Section 5.2) are used as the initial population for NSGA-II. In order to work with feasible solutions, penalization is used to avoid selecting infeasible solutions. After normalizing the objectives, penalty factors where used in each objectives.

In Figure 5.5, the results for different thresholds at \$784M budget constraint is displayed. It can be seen how the ranges of the curves changes for each threshold. The Table 5.11 shows the minimum, maximum values and range for the objectives for the \$784M budget for different threshold values. It can be observed that in general larger threshold values gives smaller ranges for direct economic loss as well as population dislocation.

Figure 5.6 shows for budget \$784 and threshold 0.35 the converted ϵ-solution and the NSGA-II solution. It can be seen that the converted solution serves well as a initial population for NSGA-II. Additionally, a point D is selected to show the reduction in both objectives as shown in Table 5.13.

The hypervolume indicator explained in Section 3.2 is calculated for each threshold. The objectives are normalized and the reference point is (1.1, 1.1). The obtained values are shown in Table 5.12. As seen in Figure 3.1, higher values of threshold results in solutions near the origin.

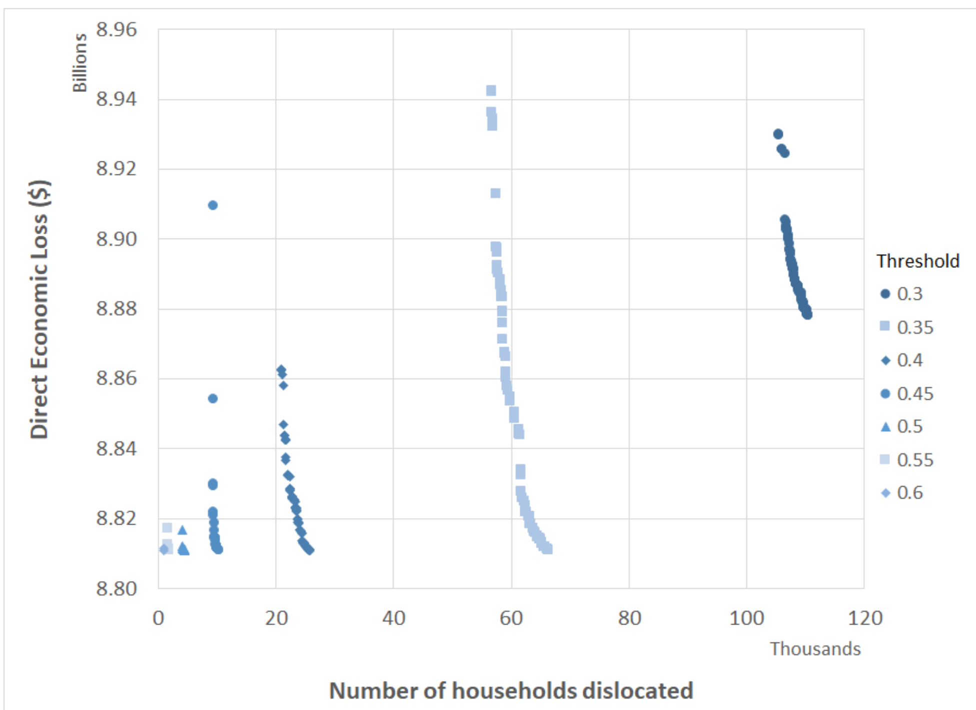

Figure 5.5: Results of NSGA-II for $784 budget constraint for different thresholds

In Figure 5.7, the NSGA-II solutions for budget constraint $784M for different thresholds were transformed to linear population dislocation and compare to the linear solution. It can be observed that the transformed solutions are dominated by the linear Pareto front.

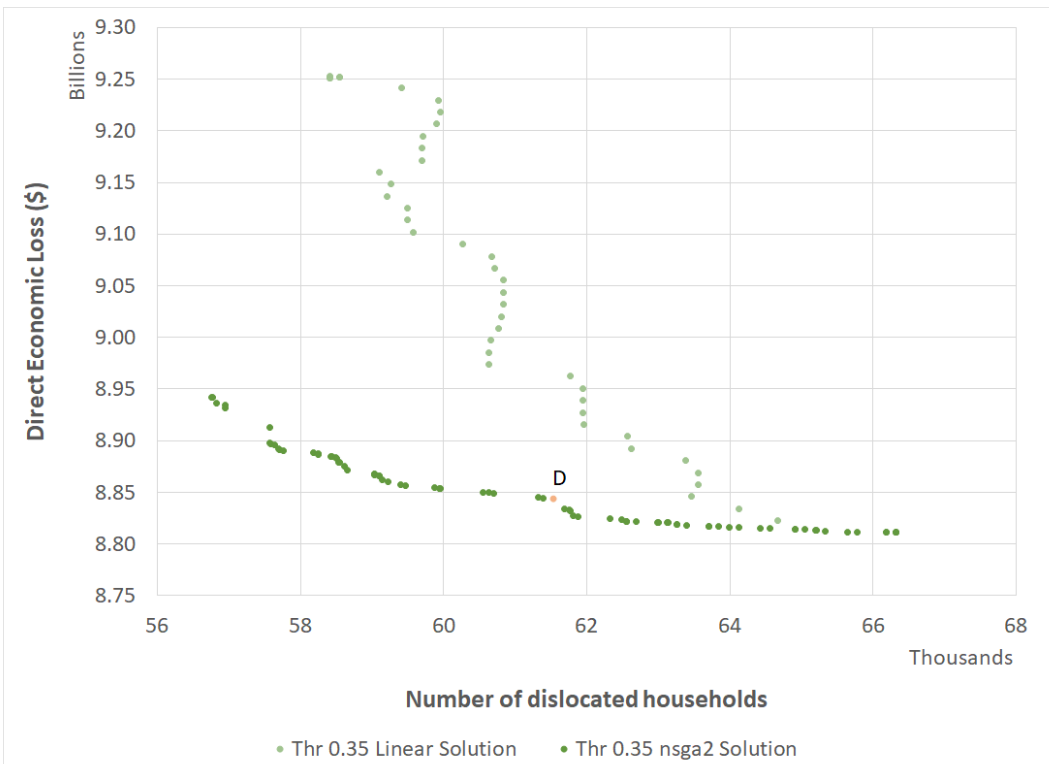

Figure 5.6: For budget $784M, the solution for NSGA-II with threshold 0.35 and the solution of ϵ-constraint are shown

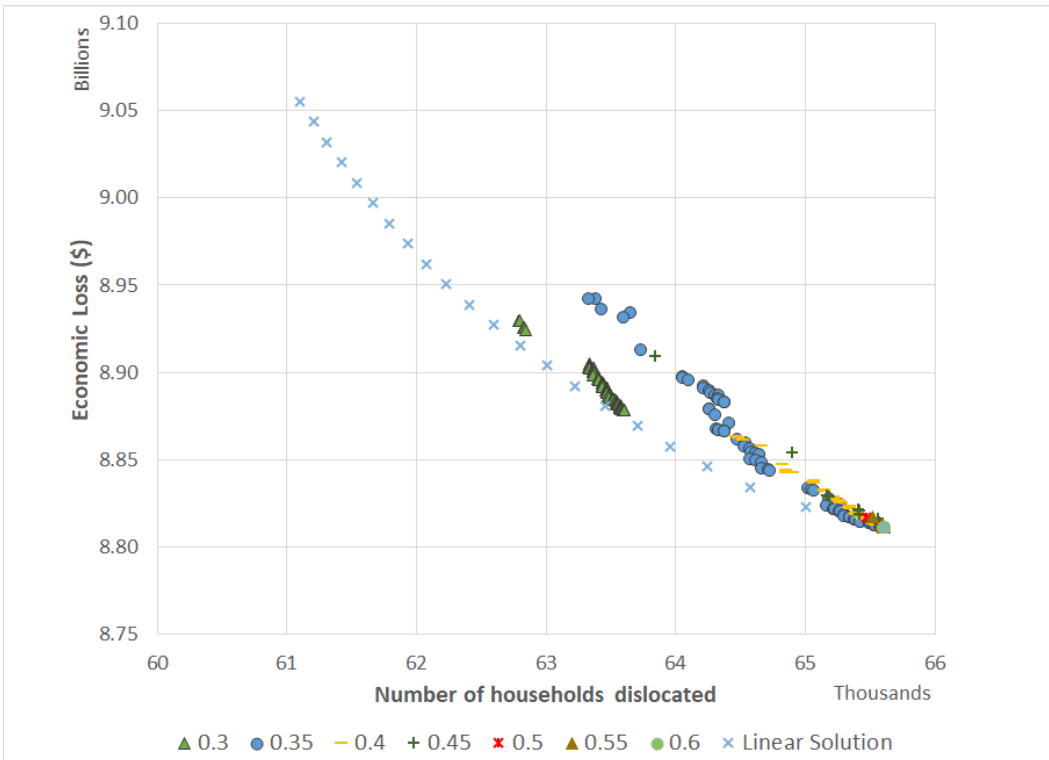

Figure 5.7: NSGA-II solutions for budget constraint $784M transformed to linear population dislocation

5.4. Comparison

For the initial values of population dislocation, for the linear model it represents 24.8% of total households whereas for the nonlinear model it varies from 0.6% to 37.7% as shown in Table 5.3 and 5.7 in the analyzed range. The threshold 0.35 gives a value of 24.5% which is the closest to the linear model result.

Comparing the initial distributions of population dislocation by PUMA of linear and nonlinear with threshold 0.35. The distribution for each PUMA changes, e.g. for linear population dislocation of PUMA 3202, 29.8% of the households for that PUMA are dislocated whereas with the nonlinear model, 51.6% of them dislocate. Another difference to point out is for PUMA 3208, where for the linear model 20.1% of the households are dislocated whereas for the nonlinear only 0.2%.

For the initial distribution according to income level, for medium income level there is a slight difference, for nonlinear the number of dislocated households is 2.4% more. For low income, the number of dislocated household for the nonlinear model is almost half of the linear dislocation. Finally, for high income is 51.8% whereas for nonlinear 36%.

Now, I will proceed to make a comparison among the solution for budget $784M. Recalling that the baseline direct economic loss is $11.5B. The solution of MRA that uses linear population dislocation as one objective gives a range in direct economic loss from $8.8 to $9.3 and dislocation of 60 to 65 thousands. For the case of the nonlinear the threshold that gives similar ranges is 0.35. The ranges go from $8.8 to $8.9 millions in direct economic loss and a range among 57 to 66 thousands of dislocated households. The linear MRA model gives a smaller range for economic loss; however for number of dislocated households is larger than the other.

Finally when comparing points B from 5.3 and D from 5.6. The reduction for B and D is shown in Table 5.5 and 5.13. The decrease for direct economic loss is similar; however, for dislocation there is a considerable difference of 28.6%.

Point	Direct loss % Decrease	Dislocation % Decrease
A	12.9%	78.9%
B	22.7%	82.1%
C	37.4%	86.2%

Table 5.5: Percentage reduction of points in Figure 5.3.

Budget		Minimum	Maximum	Range
$392M	Dislocation	70,675	77,316	6,641
	Loss ($ millions)	9,986	10,300	314
$784M	Dislocation	60,075	65,605	5,530
	Loss ($ millions)	8,811	9,253	442
$1.6B	Dislocation	46,314	50,783	4,469
	Loss ($ millions)	7,078	7,707	629

Table 5.6: Solution for extreme points when using linear population dislocation

% Dislocated households						
0.30	0.35	0.40	0.45	0.50	0.55	0.60
37.7%	24.5%	14.6%	8.1%	4.5%	1.8%	0.6%

Table 5.7: Initial percentage nonlinear population dislocation for several thresholds

	% Dislocated households						
PUMA	0.30	0.35	0.40	0.45	0.50	0.55	0.60
3201	36.1%	31.5%	27.0%	22.7%	15.1%	8.0%	3.0%
3202	63.2%	51.6%	36.7%	18.1%	6.9%	2.1%	0.4%
3203	23.8%	14.4%	9.9%	1.1%	0.9%	0.6%	0.0%
3204	52.3%	30.1%	15.6%	8.1%	4.4%	0.1%	0.1%
3205	43.8%	11.7%	1.6%	0.1%	0.0%	0.0%	0.0%
3206	59.6%	35.4%	10.0%	4.1%	2.1%	0.5%	0.0%
3207	12.3%	7.4%	3.0%	1.0%	0.6%	0.0%	0.0%
3208	0.5%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%

Table 5.8: Initial percentage nonlinear population dislocation distribution by PUMA

	% Dislocated households						
Income Level	0.30	0.35	0.40	0.45	0.50	0.55	0.60
Low	16.6%	8.7%	5.2%	3.4%	2.2%	0.5%	0.2%
Medium	43.8%	30.2%	19.7%	10.8%	6.2%	2.8%	0.9%
High	84.5%	51.8%	20.1%	10.7%	3.4%	1.2%	0.5%

Table 5.9: Initial percentage nonlinear population dislocation distribution by income level

Parameter	Value
Population	300
Number of generations	500
Type crossover	single-point
Crossover rate	0.9
Mutation rate	0.063

Table 5.10: Parameters used for NSGA-II

Threshold		Minimum	Maximum	Range
0.3	Dislocation	105,601	110,523	4,922
	Loss ($ millions)	8,878	8,930	52
0.35	Dislocation	56,763	66,318	9,555
	Loss ($ millions)	8,811	8,942	131
0.4	Dislocation	20,918	25,734	4,816
	Loss ($ millions)	8,811	8,863	52
0.45	Dislocation	9,371	10,389	1,018
	Loss ($ millions)	8,811	8,909	98
0.5	Dislocation	4,031	4,514	483
	Loss ($ millions)	8,811	8,817	6
0.55	Dislocation	1,726	1,863	137
	Loss ($ millions)	8,811	8,817	6
0.6	Dislocation	940	958	18
	Loss ($ millions)	8,811.0	8,811.6	0.6

Table 5.11: Solution for extreme points when using nonlinear population dislocation for budget constraint $784

Threshold	Hypervolume value
0.3	0.0789
0.35	0.6291
0.4	1.0109
0.45	1.1322
0.5	1.1865
0.55	1.2098
0.6	1.2178

Table 5.12: Hypervolume values for budget constraint $784 with normalized objectives with respect to point reference (1.1, 1.1) for different thresholds

Point	Direct loss % Decrease	Dislocation % Decrease
D	23.3%	53.5%

Table 5.13: Percentage reduction of point D from Figure 5.6.

Chapter 6

Conclusions

The importance of taking actions prior to a natural hazard can help to diminish life and economic losses. These actions are part of what is called mitigation in the literature. Structural retrofitting has been proven to help reduce the losses of buildings in an earthquake scenario. The models developed in this thesis aims at choosing which buildings should be retrofitted according to two objectives: direct economic loss and population dislocation. Two distinct population dislocation models are found in literature; however, it is not possible to determine which is more accurate than the other. One is a product of ordinary least squares regression and the other is the result of a logistics regression. Therefore, one is linear and the other nonlinear.

This work analyzes the use of the two population dislocation models in a mitigation resource allocation multi-objective optimization problem in an earthquake scenario. The work done by [9] and [10] are used as a basis. While they use a virtual community testbed, a real case study Shelby County in Tennessee is used for this thesis.

An important finding was the fact that a way to accelerate the convergence of the NSGA-II model was found. The use of the solutions from the MRA problem with linear population dislocation as one objective as the initial population helped to achieve the convergence faster.

Another finding when comparing the Pareto fronts of both models, it is the fact that the predictions from the linear population dislocation are more conservative, i.e. predict more than the nonlinear population dislocation for the majority of thresholds analyzed. The thresholds from 0.4-0.6 are in the left side of the Pareto front of the OLS ϵ-constraint solution.

Additionally, it can be inferred that a threshold value of 0.55 or above doesn't reflect a realistic number for the number of dislocated household (1.5% or less of the total number of households). This fact shows the need to use an adequate threshold value according the a natural hazard specific scenario as stated in literature.

Furthermore, it was found when comparing and contrasting that the total initial values for direct economic loss and population dislocations when using linear population dislocation as an objective are similar to the values when using the nonlinear population dislocation with threshold 0.35; however, the distribution by PUMA and income level differs since they take different characteristics into account.

One limitation from this thesis, it is the lack of real data to make a reliable comparison and determine if one model is better than the other. Additionally, the availability of this data would allow to select an appropriate value for the threshold parameter in the nonlinear population dislocation. An additional limitation, it is the fact that the models were developed for a specific natural hazard event.

Due to this fact, the current population dislocation models are not robust, i.e. they give not accurate predicted values for a wide range of events. The development of a robust model by the social science experts would allow to have more accurate solution for the MRA multi-objective optimization.

References

[1] D. Kalyanmoy, Multi objective optimization using evolutionary algorithms, John Wiley and Sons, 2001.

[2] NOAA National Centers for Environmental Information. (NCEI), U.S. Billion-Dollar Weather and Climate Disasters.
URL https://www.ncdc.noaa.gov/billions/

[3] Presidential Policy Directive – Critical Infrastructure Security and Resilience, Retrieved from https://obamawhitehouse.archives.gov/the-press-office/2013/02/12/presidential-policy-directive-critical-infrastructure-security-and-resil (2013).

[4] A. M. Jackman, M. G. Beruvides, Hazard Mitigation Planning in the United States: Historical Perspectives, Cultural Influences, and Current Challenges, InTech, Rijeka, 2013, p. Ch. 03.

[5] Federal Emergency Management Agency, Earthquake Hazard Mitigation Handbook, 2002.

[6] H. Shah, F. Bendimerad, P. Stojanovski, Resource allocation in seismic risk

mitigation, in: Proceedings 10th World Conference on Earthquake Engineering, Madrid, Vol. 4, 1992, pp. 6007–6011.

[7] E. Jennings, J. van de Lindt, L. Peek, Multi-objective community-level seismic retrofit optimization for resiliency using engineering and socioeconomic variables, in: 12th International Conference on Applications of Statistics and Probability in Civil Engineering, Vancouver, Canada, pp. 1–10.

[8] A. Dodo, N. Xu, R. A. Davidson, L. K. Nozick, Optimizing regional earthquake mitigation investment strategies, Earthquake Spectra 21 (2) (2005) 305–327.

[9] W. Zhang, C. Nicholson, A multi-objective optimization model for retrofit strategies to mitigate direct economic loss and population dislocation, Sustainable and Resilient Infrastructure 1 (3-4) (2016) 123–136.

[10] M. Snelling, Model for mitigating economic and social disaster damage through structural reinforcement, Master thesis, University of Oklahoma (2017).

[11] B. R. Ellingwood, H. Cutler, P. Gardoni, W. G. Peacock, J. W. van de Lindt, N. Wang, The Centerville Virtual Community: a fully integrated decision model of interacting physical and social infrastructure systems, Sustainable and Resilient Infrastructure 1 (3-4) (2016) 95–107.

[12] W. Peacock, Y.-S. Lin, J. Lu, Y. Zhang, Household Dislocation Algorithm 2: An OLS through the Origin Approach, Report, Hazard Reduction and Recovery Center, Texas A&M University (2008).
URL `http://hrrc.arch.tamu.edu/publications/research%20reports/08-04R%20Dislocation%20Algorithm%2022.pdf`

[13] Y.-S. Lin, W. Peacock, J. Lu, Y. Zhang, Household dislocation algorithm 3: A logistic regression approach, Report, Hazard Reduction and Recovery Center, Texas A&M University (2008).
URL http://hrrc.arch.tamu.edu/publications/research%20reports/08-05R%20Dislocation%20Algorithm%2034.pdf

[14] Y.-S. Lin, Development of algorithms to estimate post-disaster population dislocation–a research-based approach, Thesis, Texas A&M University (2009).
URL http://hdl.handle.net/1969.1/ETD-TAMU-2009-08-3266

[15] W. G. Peacock, H. Gladwin, B. H. Morrow, Hurricane Andrew: Ethnicity, gender and the sociology of disasters, Routledge, 2012.

[16] M. K. Lindell, C. S. Prater, Assessing community impacts of natural disasters, Natural hazards review 4 (4) (2003) 176–185.

[17] E. Quarantelli, Sheltering and housing after major community disasters: Case studies and general observations, Report, Ohio State university research foundation Columbus (1982).

[18] K. Miettinen, Nonlinear multiobjective optimization, Springer Science & Business Media, 1999.

[19] K. Deb, S. Agrawal, A. Pratap, T. Meyarivan, A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II, in: International conference on parallel problem solving from nature, Springer, Berlin, Heidelberg, pp. 849–858.

[20] B. Huang, B. Buckley, T.-M. Kechadi, Multi-objective feature selection by

using NSGA-II for customer churn prediction in telecommunications, Expert Systems with Applications 37 (5) (2010) 3638–3646.

[21] H. Ishibuchi, Y. Sakane, N. Tsukamoto, Y. Nojima, Evolutionary many-objective optimization by NSGA-II and MOEA/D with large populations, in: 2009 IEEE International Conference on Systems, Man and Cybernetics, IEEE, San Antonio, Texas, USA, 2009, pp. 1758–1763.

[22] J. D. Knowles, L. Thiele, E. Zitzler, A tutorial on the performance assessment of stochastic multiobjective optimizers, Report, TIK (2006).
URL `http://hdl.handle.net/20.500.11850/23822`

[23] J. J. Durillo, J. GarcÃa-Nieto, A. J. Nebro, C. A. C. Coello, F. Luna, E. Alba, Multi-objective particle swarm optimizers: An experimental comparison, in: International conference on evolutionary multi-criterion optimization, Springer, pp. 495–509.

[24] W.-F. Leong, G. G. Yen, Pso-based multiobjective optimization with dynamic population size and adaptive local archives, IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 38 (5) (2008) 1270–1293.

[25] G. Minella, R. Ruiz, M. Ciavotta, A review and evaluation of multiobjective algorithms for the flowshop scheduling problem, INFORMS Journal on Computing 20 (3) (2008) 451–471.

[26] E. Zitzler, L. Thiele, Multiobjective evolutionary algorithms: a comparative case study and the strength pareto approach, IEEE Transactions on Evolutionary Computation 3 (4) (1999) 257–271. `doi:10.1109/4235.797969`.

[27] U.S. Census Bureau, Block Groups, Accessed: 30 March 2019.
URL https://www.census.gov/programs-surveys/geography/about/glossary.html#par_textimage_4

[28] Hazus, Earthquake Loss Estimation Methodology, Technical manual, National Institute of Building for the Federal Emergency Management Agency, Washington (DC).

[29] U.S. Census Bureau, American FactFinder, Accessed: 30 March 2019.
URL https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml

[30] W. Zhang, P. Lin, N. Wang, C. Nicholson, X. Xue, Probabilistic prediction of postdisaster functionality loss of community building portfolios considering utility disruptions, Journal of Structural Engineering 144 (4) (2018) 04018015.